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Improvement of coal mine roof rating classification using fuzzy type-2

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Abstract
One of the main concerns of an underground coal mining engineer is the safety and stability of the mine. One way that the safety and stability can be ensured is to know and understand the coal mine geology and how it reacts to the mining process. One technique that has shown a lot of success in the coal mining industry for geologic technical evaluation purposes is the coal mine roof rating (CMRR). The CMRR classification is based on geotechnical data taken from the immediate roof layers within the mine. Since the uncertainty exists in geotechnical data, and CMRR process depends on the expert's idea implicitly, the final value may be inaccurate. In this paper, the fuzzy type 2 is used to overcome this uncertainty. To design the fuzzy system for calculating the CMRR, only quantitative variables (UCS, spacing, and persistence) are considered as fuzzy inputs. Finally, the scores of CMRR and FCMRR for four units of Riccall mine are compared.

Keywords: *CMRR, Fuzzy Type-2, Coal Mines, FCMRR.*

1. Introduction

One of the main goals of a mining engineer is to guarantee the safety, stability, and productivity of the mine. The stability of the mine opening is of major concern because it directly influences both the safety and productivity of the entire mining system [1]. A mining engineer's main concern regarding mine stability is to reduce and prevent roof and rib falls from occurring. The ability of the mining engineer to observe and possibly predict the changing geology, along with its effect on the roof stability, is one of the most useful skills to increase mine safety and productivity [2].
Over the years, many useful tools have been created to help the mine engineer in analyzing and interpreting geologic and structural mine features. One tool that was developed to specifically evaluate the competence of coal mine roof rock is the Coal Mine Roof Rating (CMRR) [1, 3-5]. Since its inception, CMRR has been used very successfully throughout the world in the evaluation of the competency of coal mine roof rock [4, 5]. The value of CMRR is calculated based on four parameters including: the uniaxial compressive strength (UCS) of the intact rock, the intensity (spacing and persistence) of discontinuities such as bedding planes and slickensides, the shear strength (cohesion and roughness) of discontinuities, and the moisture sensitivity of the rock [6]. Many researchers used CMRR parameter in their study [7, 4, 8-12].
On the other hand, uncertainty plays a critical role in geotechnical design projects. In addition to the natural variability of geomaterials, knowledge-based uncertainty involving testing, transformation and modeling errors must also be considered to develop an accurate geomechanical model [13]. Consequently, several approaches have been suggested to deal with uncertainty. The fuzzy logic approach has been proposed as an objective tool to overcome this uncertainty [14].
After introducing the fuzzy method, this method have been applied successfully to most rating based rock engineering classifications such as RMR [15-17], GSI [18, 19], RME [20]. The CMRR classification assigns quantifiable values to predefined classified parameters of a rock mass.

In this classification, assigning a single value rather than a range to each parameter is a source of uncertainty. Therefore, using a proper technique which can simultaneously take both the complexity and inherent uncertainty is very beneficial. Fuzzy logic is a useful mathematical tool for modeling the existing uncertainty and complexity [11].

Type-1 fuzzy logic has been used successfully in a wide range of problems such as control system design, decision making, classification, system modelling and information retrieval [21-23, 10, 24-28]. However, type-1 approach can not directly model uncertainties and minimize its effects [29]. Therefore, existence of uncertainties in most real-world applications makes the use of type-1 fuzzy logic inappropriate in many cases.

Problems related to modelling uncertainty using crisp membership functions of type-1 fuzzy sets have been recognized early, and Zadeh [30] introduced higher types of fuzzy sets called type-2 [31, 32]. Type-2 fuzzy sets embed a large number of type-1 fuzzy sets to describe variables with a detailed description, and can handle numerical and linguistic uncertainties because its membership function is fuzzy and has a footprint of uncertainty (FOU), while type-1 fuzzy sets membership function is precise [33]. Many researchers used fuzzy type-2 in their studies [34-38].

In this paper, to overcome these uncertainties, a fuzzy type-2 is applied to CMRR classification. To design the fuzzy system for calculating the CMRR, only quantitative variables are considered as fuzzy inputs. The fuzzy system output is then added to the score obtained from qualitative variables. Finally, the Riccal mine is chosen as a case study, and crisp CMRR and FCMRR (fuzzy CMRR) are calculated for panel H438 at 214 metre mark of this mine.

2. CMRR Method

The CMRR was developed by the USBM in 1994 as a means to mechanistically quantify bedded coal mine roof rock, and to improve the safety and design of U.S. coal mines [1]. This system quantitatively describes the geotechnical aspects of the mine roof rather than recording a detailed lithology. The CMRR has the same format as Bieniawski's RMR [39], summing various individual ratings to obtain a final CMRR on a scale of 0 to 100. The classification was developed to be applicable to all coal measure rocks regardless of depositional environment, age, rank or geographical location [40].

2.1. CMRR Determination

To determine the CMRR, the mine roof is first divided into structural units at least 15cm thick [1]. A rating is then determined for each unit based primarily on an evaluation of the CMRR components which include:

- **Compressive Strength**

One of the critical parameters of the CMRR is the compressive strength of each unit. This parameter is important because the compressive strength determines the ability of the unit to anchor a bolt and to allow fractures to form within the unit. Laboratory testing is generally considered the standard method of determining the UCS [1]. The strength rating scale used in the CMRR classification is shown in Table 1.

Table 1. Strength rating [1].

Strength (MPa)	Rating
>103	30
55 to 103	22
21 to 55	15
7 to 21	10
<7	5

- **Discontinuity Intensity**

The intensity of the discontinuities is determined by measuring the spacing and the persistence of the similar discontinuities within a unit. The spacing is measured by finding the average distance between each discontinuity within a discontinuity set. The persistence of a discontinuity set is the measure of the size of the discontinuity set plane in both vertical and horizontal direction. A discontinuity set with very wide spacing that does not cover much area has little consequence to the mine roof, whereas a discontinuity set that is either closely spaced or covers a wide area can cause severe problems regarding roof control. Similar to the roughness and cohesion parameters, the intensity of the discontinuities can also account for up to 35% of the final CMRR [1]. Table 2 shows the bedding /discontinuity rating scale for CMRR classification.

Tbale 2. Spacing- persistence rating [1].

Persistence (m)		Spacing (1)	(2)	(3)	(4)	(5)
		>1.8 m	0.6 to 1.8 m	20 to 61 cm	< 6 to 20 cm	< 6 cm
(1)	0 to 1	35	30	24	17	9
(2)	1 to 3	32	27	21	15	9
(3)	> 3	30	25	20	13	9

- **Moisture Sensitivity**

The moisture sensitivity of the rocks present in the mine roof can greatly affect their competence when water and/or high humidity is present in the mining environment. Although some roof rock has little or no reaction to water, some clay stones and mud stones react poorly to the presence of water. They may swell or lose all competence as a roof material. The moisture sensitivity is determined through visual estimation along with water immersion testing over a 24-hour period, and a moisture adjustment to the CMRR is assigned accordingly [1]. Table 3 shows the moisture sensitivity rating scale for CMRR classification.

Tbale 3. Moisture sensitivity rating [1].

	Moisture Sensitivity	Rating
(1)	Not sensitive	0
(2)	Slightly sensitive	-3
(3)	Moderately sensitive	-10
(4)	Severely sensitive	-25

- **Shear Strength of Discontinuity**

In order to determine how much a discontinuity will affect the strength of the coal mine roof, both the cohesion and roughness of the discontinuity surface must be found. A low cohesion or a planar contact, and a low roughness value of a discontinuity surface can greatly reduce the ability of the rock to resist lateral movement. The shear strength of the discontinuities is so important that it may account for up to 35% of the overall CMRR [1]. Table 4 shows the Shear Strength rating scale for CMRR classification.

2.1.1. Adjustments Factors

When all the information is gathered for each unit, to obtain the CMRR for the roof as a whole, first, each of the unit ratings is multiplied by the thickness of that unit. These ratings are then summed and then divided by the total thickness to produce a thickness weighted rating for the roof. Adjustments are then made to the thickness weighted rating to account for strong beds, unit contacts, groundwater and surcharge [1]. In Figure 1, the process of CMRR calculation is shown.

The adjustments value for strong beds, unit contacts, groundwater and surcharge are shown in Tables 5 to 8. The CMRR can be divided into 3 classes which are weak (CMRR 0-40), moderate (CMRR 40-60) and strong (CMRR 60-100) [1].

Tbale 4. Cohesion- roughness rating [1].

Roughness		Cohesion (1)	(2)	(3)	(4)
		Strong Cohesion	Moderate Cohesion	Weak Cohesion	Slickenside
(1)	Jagged	35	29	24	10
(2)	Wavy	35	27	20	10
(3)	Planar	35	25	16	10

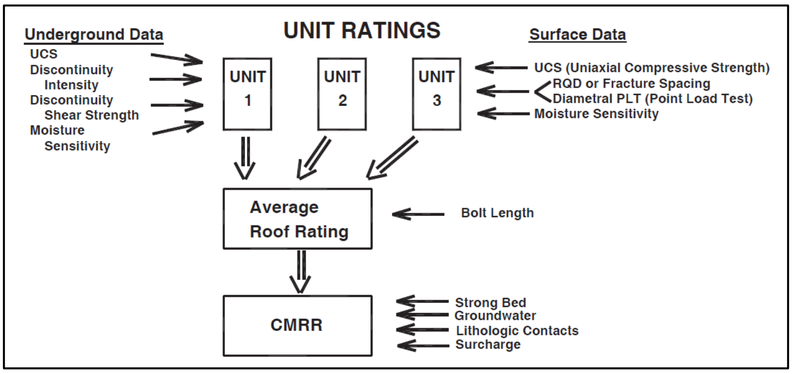

Figure 1. Flowchart for the CMRR [6].

Table 5. Strong bed adjustment [1].

Thickness of Strong Bed (m)	Storong Bed Difference							
	5-9	10-14	15-19	20-24	25-29	30-34	35-34	>40
0.3 to 0.6	0	2	4	5	7	8	9	10
0.6 to 0.9	2	4	7	9	12	14	17	20
0.9 to 1.2	3	5	10	14	18	21	25	30
>1.2	4	8	13	18	23	28	34	40

Table 6. Unit contacts adjustment [1].

Number of major contact	Adjustment
0	0
1 to 2	-2
3 to 4	-4
>4	-5

Table 7. Groundwater adjustment [1].

Condition	Adjustment
Dry	0
Damp	-2
Light Drip	-4
Heavy Drip	-7
Flowing	-10

Table 8. Surcharge adjustment [1].

Condition	Adjustment
Upper units approximately equal in strength to bolter interval	0
Upper units significantly weaker than bolted interval	-2 to -5

3. Fuzzy type-2

Type-2 Fuzzy Sets (FSs) were introduced by Zadeh in 1975 [30] as an extension of Type-1 FSs, but it gained much more attention recently with the several developments proposed by Mendel and Karnik [41]. Type-1 FSs introduced an important fuzziness degree to create linguistic partitions of a crisp domain. Nonetheless, the MFs used to do so are themselves crisp since they are totally defined without considering any uncertainty on their parameters. Type-2 FS overcome this limitation by defining a secondary degree of fuzziness, i.e. the membership value for each input of a FS is itself defined as a FS in the [0,1] domain. For better illustration, consider the process of defining a concept as a Type-1 FS by polling a group of experts. When all responses are collected, it will certainly be noticed that the endpoints of the membership function will vary from person to person. The union of all embedded Type-1 FSs eventually will end up in a blurred area, known as Footprint of Uncertainty (FOU), that is bounded by two MFs, namely the Upper Membership Function (UMF) and the Lower Membership Function (LMF). Furthermore, each membership function given by a person can be assigned a variable weight according to the amount of confidence associated to its opinion, defining this way the secondary degree of fuzziness. For this reason, a Type-2 FS representation embeds additional degrees of freedom which can better handle uncertainties caused by noisy data and changing environments as is required for example when developing a process's model. Figure 2 gives a better overview of the new concepts introduced by Type-2 FS.

However, the additional degree of freedom results in increasing the computational complexity. To cope with this problem, a simplified model of fuzzy type 2 is introduced, known as Interval Type-2 Fuzzy Sets (IT2FSs) in which each fuzzy set is characterized solely by its lower membership function (LMF) and upper membership function (UMF).

The structure of a Type-2 FLS has the same components of its Type-1 counterpart, namely: a Fuzzifier, a Rule-Base, an Inference Engine and ultimately the Output Processor. While in Type-1 FLSs their final stage resumes to a defuzzification procedure, in the Type-2 case, the Output Processor embraces an additional stage, so a Type-2 FS is firstly converted into an equivalent Type-1 FS. This work is performed by a Type-Reduction (TR) algorithm. The structure of fuzzy type 2 system is depicted in Figure 3 [43].

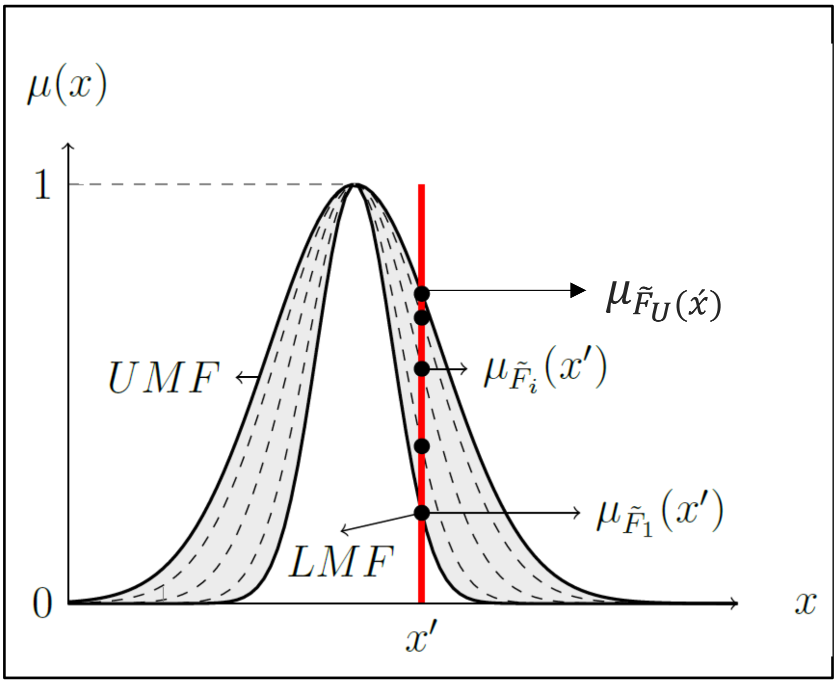

Figure 2. Type 2 Fuzzy sets. Lower membership function and upper membership function are defined by LMF and UMF [42].

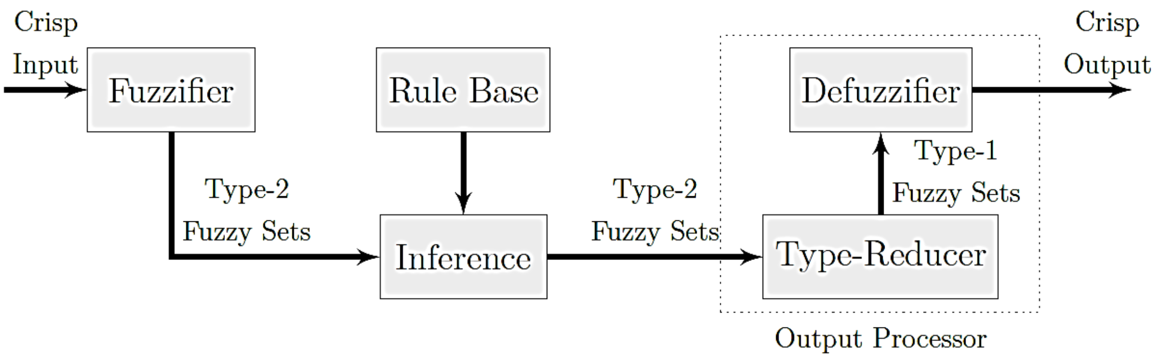

Figure 3. The structure of Type 2 Fuzzy Logic Systems (T2FLS) [43].

The main difference between a Type-1 FLS and a Type-2 FLS resides in their inference engine. The result of the input and corresponding antecedent operations in the ith rule in Type-1 FLS yields a crisp number referred as membership degree. In an IT2FS the result of this operation is an interval. Consider the fuzzy type 2 rule base in the following form [43]:

$R^n : IF\ x_1\ is\ \tilde{X}_1^n$ and…. And

$$x_I\ is\ \tilde{X}_I^n, THEN\ y\ is Y^n, \quad n = 1,2,\ldots,N \tag{1}$$

where N is the number of rules, $\tilde{X}_i^n$ (i=1,2,…I), are IT2 FSs, I is the number of system inputs and $Y^n = \left[\underline{y}^n, \bar{y}^n\right]$ is an interval which can be introduced as consequent part of Takagi Sugeno type fuzzy systems, or the center of output fuzzy type 2 membership functions in Mamdani systems.

Given input $X' = \left(x'_1, x'_2, \ldots, x'_I\right)$, every rule is fired by an interval weight introduced as $F^n\left(X'\right)$.

$$F^n\left(X'\right) = \left[\mu\underline{X}_1^n\left(x'_1\right)\times\ldots\times\mu\underline{X}_I^n\left(x'_I\right), \quad \mu\bar{X}_1^n\left(x'_1\right)\times\ldots\times\mu\bar{X}_I^n\left(x'_I\right)\right] \equiv \left[\underline{f}^n, \bar{f}^n\right], \text{ n=1,2,..., N} \tag{2}$$

Now, type reduction methods should be performed to combine $F^n\left(X'\right)$ and consequents part of rules. The center of sets type reducer is commonly used for this purpose [43]:

$$Y_{cos}\left(X'\right) = \bigcup_{\substack{f^n \in F^n\left(X'\right) \\ y^n \in Y^n}} \frac{\sum_{n}^{N} f^n y^n}{\sum_{n=1}^{N} f^n} = [y_l, y_r] \qquad (3)$$

Where y_l and y_r are calculated by Karnik-Mendel (KM) algorithm in [42] which is not discussed more in this paper. Finally, the defuzzified output can be determined as [43]:

$$y = \frac{y_r + y_l}{2} \qquad (4)$$

In the following section, the fuzzy type-2 CMRR calculation system is discussed.

4. Fuzzy type II CMRR calculation

Since the boundary of different classes of CMRR inputs, such as UCS and Spacing, are not crisp, and different experts have different ideas about the bounds of fuzzified inputs, fuzzy type 2 system can be very useful in this area. To design the fuzzy system for calculating the CMRR, only quantitative variables (UCS, Spacing, and Persistence) are considered as fuzzy inputs. The fuzzy system output is then added to the score obtained from qualitative variables (moisture, cohesion and roughness) according to Table 3 and 4. The type-2 FSs introduced for fuzzy system inputs are displayed in Figures 4-6.

The proposed fuzzy system is Takagi-Sugeno type, and the consequent part of rules are intervals. Considering the number of MFs introduced for system input, we have 75 rules $(5 \times 5 \times 3 = 75)$ which should be determined. The rules are designed based on crisp score defined in Table 1 and 2. The type-2 Takagi-Sugeno fuzzy systems rule base is introduced in Tables 9-11. The structure of the proposed fuzzy system is displayed in Figure 7.

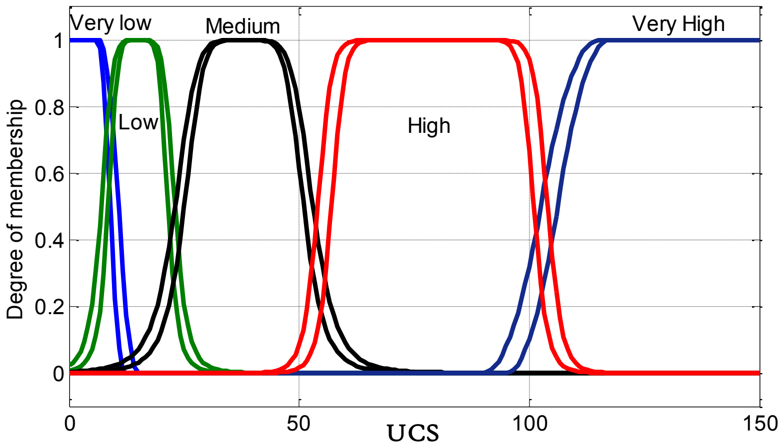

Figure4. Type 2 fuzzy sets for input variable "UCS".

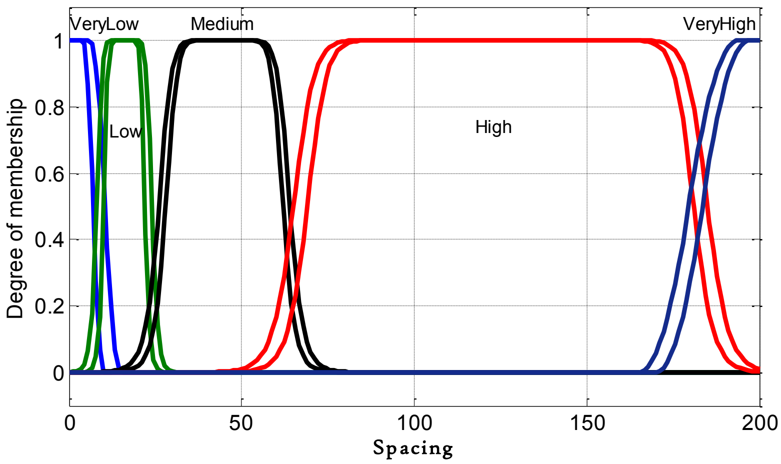

Figure 5. Type 2 fuzzy sets for input variable "Spacing".

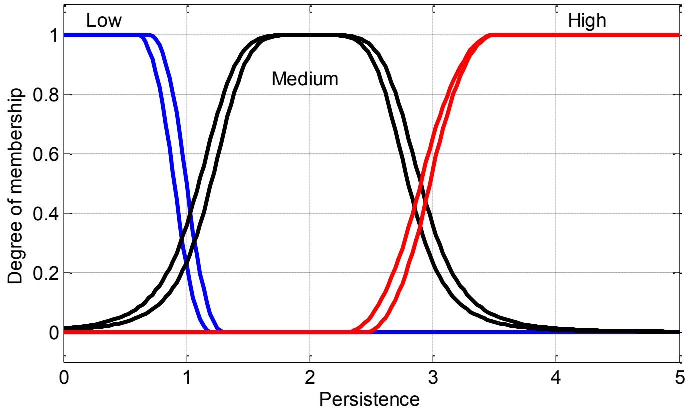

Figure 6. Type 2 fuzzy sets for input variable "Persistence".

Table 9. Type 2 Takagi- Sugeno Fuzzy system rule base. Persistence is considered as "low".

Spacing \ UCS	Very Low	Low	Medium	High	Very high
Very Low	[13 15]	[18 20]	[23 25]	[30 32]	[38 40]
Low	[21 23]	[26 28]	[31 33]	[38 40]	[46 48]
Medium	[28 30]	[33 35]	[38 40]	[45 47]	[53 55]
High	[34 36]	[39 41]	[44 46]	[51 53]	[59 61]
Very high	[39 41]	[44 46]	[49 51]	[56 58]	[64 66]

Persistence is low

Table 10. Type 2 Takagi- Sugeno Fuzzy system rule base. Persistence is considered as "Medium".

Spacing \ UCS	Very Low	Low	Medium	High	Very high
Very Low	[13 15]	[18 20]	[23 25]	[30 32]	[38 40]
Low	[19 21]	[24 26]	[29 31]	[36 38]	[44 46]
Medium	[25 27]	[30 32]	[35 37]	[42 44]	[50 52]
High	[31 33]	[36 38]	[41 43]	[48 50]	[56 58]
Very high	[36 38]	[41 43]	[46 48]	[53 55]	[61 63]

Persistence is Medium

Table 11. Type 2 Takagi- Sugeno Fuzzy system rule base. Persistence is considered as "High".

Spacing \ UCS	Very Low (5)	Low (10)	Medium (15)	High (22)	Very high (30)
Very Low	[13 15]	[18 20]	[23 25]	[30 32]	[38 40]
Low	[17 19]	[22 24]	[27 29]	[34 36]	[42 44]
Medium	[24 26]	[29 31]	[34 36]	[41 43]	[49 51]
High	[29 31]	[34 36]	[39 41]	[46 48]	[54 56]
Very high	[34 36]	[39 41]	[44 46]	[51 53]	[59 61]

Persistence is High

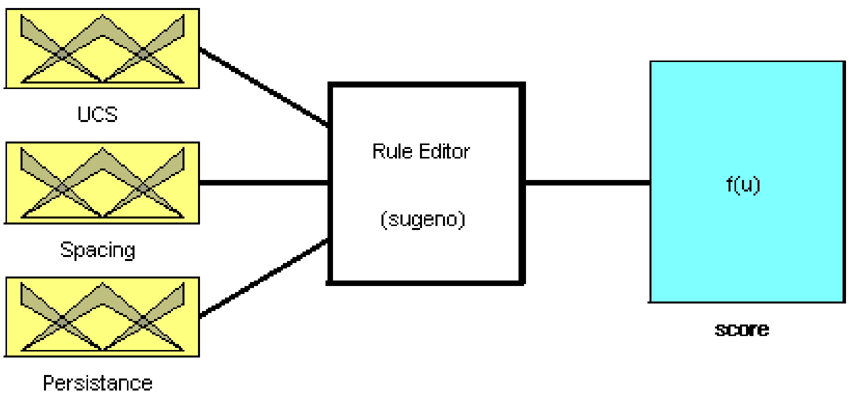

Figure 7. Structure of the proposed type 2 fuzzy system for calculation CMRR.

The output of the fuzzy system is the sum of scores corresponding to UCS, Spacing and Persistence. The final CMRR is calculated by adding the score of qualitative variables (Moisture and Shear strength of discontinuities) to the fuzzy system output.

5. Application of F-CMRR

To illustration the FCMMR application, the Riccall mine is considered as the case study. Riccall mine forms one of the six mines that comprise the Selby complex which is situated in the Vale of York to north of the town of Selby. All the mines in the complex work the Barnsley seam which varies between 300 meters' depth in the west of the area to approximately 1000 meters at the North Selby, Riccall and Whitemoor mines in the east and north of the complex [44].

Riccall mine started production in 1988 and by 1993 was producing coal at the rate of 2.5 million tons a year. The depth of cover varies from 600 to 1100 meters across Riccall's reserve area and the thickness of the Bamsley seam varies from 1.9 to 2.4 meters. Like all mines within the Selby complex, coal is extracted using retreat mining techniques. Case study information and roof rock cores were obtained for a total of twelve localities within the gate roads. The usage data are from roadway roof of panel H438 at 214 metre mark [45]. The summary of the geological and geotechnical information and final value of CMRR are shown in Table 12. The roof stratigraphic of 4 units are shown in Table 13.

To calculate the CMRR by the proposed method, the quantitative variables firstly applied to type 2 fuzzy system. The presented fuzzy system computes the score of three variables UCS, Spacing and Persistence. So, the input vector for 4 units of presented case study will be [41 100 4] for unit 1, [48 100 4] for unit 2, [57 100 0.9] for unit 3 and [53 100 0.9] for unit 4. The inputs are applied to fuzzy system, and the results in compare with crisp score of CMRR are presented in Table 14.

Table 12. Classification data sheet of panel H438 at 214 metre mark [45].

	Unit Number	1	2	3	4
	Height above seem roof	0.12 to 0.72	0.72 to 1.1	1.1 to 4	4 to 5
	UCS (MPa)	41	48	57	53
Bedding Properties	Bed spacing (m)	0.017	0.031	0.038	0.031
	Topography	Planar	Planar	Planar	Planar
	Roughness (JRC)	4	4	4	4
	Cohesion	0	0	0	0
	Parting planes	25	28	3	15
Joint Persistence	Set 1 (m)	4	4	0.9	0.9
	Set 2 (m)	4	4	0.9	0.9
Joint Roughness	Set 1	Slightly Rough	Slightly Rough	Slightly Rough	Slightly Rough
	Set 2	Slightly Rough	Slightly Rough	Slightly Rough	Slightly Rough
Average Spacing	Set 1 (mm)	1000	1000	1000	1000
	Set 2 (mm)	1000	1000	1000	1000
	Set 3 (mm)	1000	1000	1000	1000
Moisture sensitivity	Not Required (Dry)	*	*	*	*
CMRR		**50**	**50**	**62**	**55**

Table 13. description of roof stratigraphic of 4 units [45].

Unit	Distance above top of coal seam (m)	Description
1	0.12 to 0.72	MUDSTONE: grey many parting horizons, occasional smooth districted low angle joint
2	0.72 to 1.1	MUDSTONE: grey, silty occasional low angle joint,
3	1.1 to 4	MUDSTONE: grey, silty, Fissile parting band at 1.47 to1.49
4	4 to 5	MUDSTONE: grey, silty, frequent parting planes

Table 14. Final score of CMRR and FCMMR.

Unit number	1	2	3	4
Fuzzy system input vector [UCS Spacing Persistence]	[41 100 4]	[48 100 4]	[57 100 0.9]	[53 100 0.9]
Fuzzy system output	40.002	40.05	49.0826	47.76
Final fuzzy CMRR	50.002	50.05	59.0826	57.76
FCMRR Classification	**Moderate**	**Moderate**	**Moderate**	**Moderate**
Crisp CMRR	50	50	62	55
CMRR Classification	**Moderate**	**Moderate**	**Strong**	**Moderate**

It should be noticed that for units 1 and 2, the value of fuzzy CMRR is very close to crisp CMRR. This is because the values of inputs are in the middle of predetermined classes. For example, UCS equal to 41 only belongs to the fuzzy "Medium" set with membership value equal to 1. It is the same for UCS equal to 48 in unit 2. The spacing equal to 100 only activates the "High" set and Persistence equal to 4 belongs to "High" set. Therefore, one rule is just fired with this input, that is,

"If UCS is "Medium", Spacing is "High" and Persistence is "High" then fuzzy output is [39 41]. The fired weight is also equal to 1, so the system output would be equal to 40. By aggregating this score with the score of qualitative variable which is equal to 10, the final CMRR would be 50 and very close to crisp CMRR. The conditions are different for the other two units. The values of UCS and Persistence are near the boundaries. When UCS is 57, the "Medium" set is activated with membership value equal to interval [0.1 0.21] and the "High" set is also activated by membership value of [0.44 0.85]. Persistence equal to 0.9 is belong to "low" set by interval weight of [0.44 0.73] and to "Medium set with membership value of [0.16 0.26]. Therefore 4 rules are fired with different interval weights, which results to fuzzy output of 49.826. The computation is the same for unit 4. It is worth to explain that when UCS is 57, it is arranged at beginning of the upper interval class, so the crisp value is higher. But, the fuzzy value is decreased because it also belongs to lower class with a determined weight. For the fourth unit, the condition is the reverse. The UCS value is at the end of the lower class so the fuzzy CMRR value is greater than crisp CMRR value. It can be concluded that fuzzy system makes the borders softer and smoother. It can be said that the fuzzy system has balanced the expert different ideas on class boundaries.

6. Conclusions

The Coal Mine Roof Rating (CMRR) has been developed to quantify the weakness in the rock mass, and to apply a strength value which can be used for engineering design. In this paper, a type 2 Takagi-Sugeno fuzzy system is designed to calculate the CMRR. The fuzzy system just calculates the score of quantitative variables, and the qualitative variables score is then added to fuzzy value to compute the final CMRR. Since different experts have different opinions about the boundaries of classes of CMRR effecting parameters, fuzzy type-2 system can be very useful to this kind of issues. To illustrate the FCMMR application, the Riccall mine in UK is considered as a case study. The scores of FCMMR and CMRR are calculated for 4 units of panel H438 at 214 metre mark. In unit 1 and 2, the final score of FCMMR (50.002, 50.05) and CMRR (50, 50) are the same. In the unit 3 and 4, the final score of FCMRR (59.082, 57.76) and CMRR (62, 55) are different. In the unit 3, the FCMRR value is lower than CMRR value, and in unit 4, the value of FCMRR is more that the CMRR value. The final results of fuzzy system can demonstrate how the fuzzy system smooths the boundaries.

Reference

[1]. Molinda, G. and Mark, C. (1994). Coal Mine Roof Rating (CMRR): A practical rock mass classification for coal mines. Information circular/1994. Bureau of Mines, Pittsburgh, PA (United States). Pittsburgh Research Center.

[2]. Sherizadeh, T. and Kulatilake, P.H. (2016). Assessment of roof stability in a room and pillar coal mine in the US using three-dimensional distinct element method. Tunnelling and Underground Space Technology. 59: 24-37.

[3]. Molinda, G.M. and Mark, C. (1996). Rating the strength of coal mine roof rocks. In: Rock Mechanics Tools and Techniques: Proceedings of the 2nd North American Rock Mechanics Symposium: NARMS'96, a Regional Conference of ISRM, Montréal, Québec, Canada, 19-21 June 1996. Taylor & Francis US. 413 P.

[4]. Molinda, G.M., Mark, C. and Debasis, D. (2001). Using the coal mine roof rating (CMRR) to assess roof stability in US coal mines. Journal of mines, metals and fuels. 49: 314-321.

[5]. Mark, C., Molinda, G.M. and Barton, T.M. (2002). New developments with the coal mine roof rating. In: Proceedings of the 21st International Conference on Ground Control in Mining. Morgantown, WV: West Virginia University. pp. 294-301.

[6]. Mark, C. and Molinda, G. (2005). The coal mine roof rating (CMRR)- a decade of experience. International Journal of Coal Geology. 64: 85-103.

[7]. Rusnak, J. (1998). Application of the coal mine roof rating, derived from drill core, in the roof support design of a coal belt conveyor tunnel. In: Proc. of the 17th International Conference on Ground Control in Mining, Morgantown, WV. pp. 221-230.

[8]. Gregory, M., Christopher, M. and Debasis, D. (2001). Using the coal mine roof rating (CMRR) to assess roof stability in US coal mines, Mining industry annual review. Journal of Mines, Metals and Fuels. 15: 314-321.

[9]. Deb, D. (2003). Analysis of coal mine roof fall rate using fuzzy reasoning techniques. International Journal of Rock Mechanics and Mining Sciences. 40: 251-257.

[10]. Ghasemi, E. and Ataei, M. (2013). Application of fuzzy logic for predicting roof fall rate in coal mines. Neural computing and applications. 22: 311-321.

[11]. Razani, M., Yazdani-Chamzini, A. and Yakhchali, S.H. (2013). A novel fuzzy inference system for predicting roof fall rate in underground coal mines. Safety science. 55: 26-33.

[12]. Taheri, A., Lee, Y. and Medina, M.A.G. (2017). A modified coal mine roof rating classification system to design support requirements in coal mines. Journal of The Institution of Engineers (India): Series D. 98: 157-166.

[13]. Langford, J.C. and Diederichs, M.S. (2013). Evaluating uncertainty in intact and rockmass parameters for the purposes of reliability assessment. In: 47th US Rock Mechanics/Geomechanics Symposium, American Rock Mechanics Association.

[14]. Rafiee, R., Ataei, M. and Jalali, S.M.E. (2013). The optimum support selection by using fuzzy analytical hierarchy process method for Beheshtabad water transporting tunnel in Naien. Iranian Journal of Fuzzy Systems. 10: 39-51.

[15]. Habibagahi, G. and Katebi, S. (1996). Rock mass classification using fuzzy sets.

[16]. Ataei, M., Besheli, A.D., Sereshki, F. and Jamshidi, M. (2008). An application of fuzzy sets to the rock mass rating (RMR) system used in rock engineering; a case study in Iran. In: 8th International Scientific Conference-SGEM2008, SGEM Scientific GeoConference, pp. 347-356.

[17]. Jalalifar, H., Mojedifar, S. and Sahebi, A. (2014). Prediction of rock mass rating using fuzzy logic and multi-variable RMR regression model. International Journal of Mining Science and Technology. 24: 237-244.

[18]. Sonmez, H., Gokceoglu, C. and Ulusay, R. (2003). An application of fuzzy sets to the geological strength index (GSI) system used in rock engineering. Engineering Applications of Artificial Intelligence. 16: 251-269.

[19]. Zhang, Y.J., Cao, W.G. and Zhao, M.H. (2009). Application of fuzzy sets to geological strength index (GSI) system used in rock slope. In: Soils and Rock Instrumentation, Behavior, and Modeling: Selected Papers from the 2009 GeoHunan International Conference. pp. 30-35.

[20]. Khademi Hamidi, J., Shahriar, K., Rezai, B. and Bejari, H. (2010). Application of fuzzy set theory to rock engineering classification systems: an illustration of the rock mass excavability index. Rock mechanics and rock engineering. 43: 335-350.

[21]. Feng, F., Jun, Y.B., Liu, X. and Li, L. (2010). An adjustable approach to fuzzy soft set based decision making. Journal of Computational and Applied Mathematics, 234: 10-20.

[22]. Azarfar, A., Gholizade-Narm, H. and Shandiz, H.T. (2011). Control and synchronization of chaotic systems using fuzzy feedback linearization. In: Chaos-Fractals Theories and Applications (IWCFTA), 2011 Fourth International Workshop on, IEEE. pp. 230-234.

[23]. Daftaribesheli, A., Ataei, M. and Sereshki, F. (2011). Assessment of rock slope stability using the Fuzzy Slope Mass Rating (FSMR) system. Applied Soft Computing. 11: 4465-4473.

[24]. Chang, K.H., Chang, Y.C. and Lee, Y.T. (2014). Integrating TOPSIS and DEMATEL Methods to Rank the Risk of Failure of FMEA. International Journal of Information Technology & Decision Making. 13: 1229-1257.

[25]. Rafiee, R., Ataei, M. and KhalooKakaie, R. (2015). A new cavability index in block caving mines using fuzzy rock engineering system. International Journal of Rock Mechanics and Mining Sciences. 77: 68-76.

[26]. Karimnia, H. and Bagloo, H. (2015). Optimum mining method selection using fuzzy analytical hierarchy process- Qapiliq salt mine, Iran. International Journal of Mining Science and Technology. 25: 225-230.

[27]. Hosseini, A., Najafi, M., Shojaatlhosseini, S.A. and Rafiee, R. (2017). Determination of a suitable extraction equipment in mechanized longwall mining in steeply inclined coal seams using fuzzy analytical hierarchy method (Case study: Hamkar coal mine, Iran). Journal of Mining and Environment. 8: 487-499.

[28]. Rafiee, R., Khalookakaie, R., Ataei, M., Jalali, S.M.E., Sereshki, F. and Azarfar, A. (2016). Improvement of rock engineering system coding using

fuzzy numbers. Journal of Intelligent & Fuzzy Systems. 30: 705-715.

[29]. Mendel, J.M. and John, R.B. (2002). Type-2 fuzzy sets made simple. IEEE Transactions on fuzzy systems. 10: 117-127.

[30]. Zadeh, L.A. (1975). The concept of a linguistic variable and its application to approximate reasoning-I. Information sciences. 8: 199-249.

[31]. Ravi, V., Reddy, P. and Zimmermann, H.J. (2001). Fuzzy rule base generation for classification and its minimization via modified threshold accepting. Fuzzy Sets and Systems. 120: 271-279.

[32]. Mendel, J.M. (2003). Fuzzy sets for words: a new beginning. In: Fuzzy Systems, 2003. FUZZ'03. The 12th IEEE International Conference on, IEEE. pp. 37-42.

[33]. Mendel, J.M. (2001). Uncertain rule-based fuzzy logic systems: introduction and new directions. Prentice Hall PTR Upper Saddle River.

[34]. Torun, Y. and Tohumoğlu, G. (2011). Designing simulated annealing and subtractive clustering based fuzzy classifier. Applied Soft Computing, 11: 2193-2201.

[35]. Kahraman, C., Öztayşi, B., Sarı, İ.U. and Turanoğlu, E. (2014). Fuzzy analytic hierarchy process with interval type-2 fuzzy sets. Knowledge-Based Systems. 59: 48-57.

[36]. Kilic, M. and Kaya, İ. (2015). Investment project evaluation by a decision making methodology based on type-2 fuzzy sets. Applied Soft Computing. 27: 399-410.

[37]. Araghi, S., Khosravi, A., Creighton, D. and Nahavandi, S. (2017). Influence of meta-heuristic optimization on the performance of adaptive interval type2-fuzzy traffic signal controllers. Expert Systems with Applications. 71: 493-503.

[38]. Dhar, S. and Kundu, M.K. (2018). A novel method for image thresholding using interval type-2 fuzzy set and Bat algorithm. Applied Soft Computing. 63: 154-166.

[39]. Bieniawski, Z. (1995). Classification of rock masses for engineering: the RMR system and future trends. In: Rock Testing and Site Characterization. Elsevier. pp. 553-573.

[40]. McCulloch, C.M., Deul, M. and Jeran, P.W. (1994). Cleat in bituminous coalbeds. US Department of the Interior, Bureau of Mines.

[41]. Karnik, N.N., Mendel, J.M. and Liang, Q. (1999). Type-2 fuzzy logic systems. IEEE transactions on Fuzzy Systems. 7: 643-658.

[42]. Wu, D. (2010). A brief Tutorial on Interval type-2 fuzzy sets and systems. Fuzzy sets and systems.

[43]. Castillo, O., Melin, P., Kacprzyk, J. and Pedrycz, W. (2007). Type-2 fuzzy logic: theory and applications. In: Granular Computing, 2007. GRC 2007. IEEE International Conference on, IEEE. pp. 145-145.

[44]. Siddall, R. and Gale, W. (1992). Strata control-A new science for an old problem. Transactions of the institution of mining and metallurgy section a-mining industry. 101: A1-A12.

[45]. Whittles, D.N. (2000). The application of rock mass classification principles to coal mine design. University of Nottingham.

بهبود رتبه‌بندی روش CMRR با استفاده از روش فازی نوع ۲

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چکیده:

ایمنی و پایداری یکی از نگرانی‌های اصلی مهندسان در معادن زیرزمینی زغال‌سنگ است. یکی از راه‌هایی که می‌توان از ایمنی و پایداری اطمینان حاصل کرد، آگاهی و شناخت از خصوصیات زمین‌شناسی معادن زغال‌سنگ و نحوه رفتار لایه‌ها در حین فرآیند معدنکاری است. یکی از روش‌های که در صنایع استخراج معادن زغال‌سنگ برای ارزیابی فنی زمین‌شناسی موفقیت‌های بزرگی داشته است، رتبه‌بندی سقف معدن زغال‌سنگ (CMRR) است. این روش بر اساس اطلاعات ژئوتکنیکی که از لایه‌های سقف بلاواسطه در حین معدنکاری جمع‌آوری شده، محاسبه می‌شود. از آنجایی که داده‌های ژئوتکنیکی دارای عدم قطعیت هستند و روند محاسبه CMRR به طور ضمنی به ایده و نظر کارشناسان بستگی دارد، مقدار نهایی محاسبه شده ممکن است نادرست باشد. در این پژوهش از روش فازی نوع ۲ برای غلبه بر این عدم قطعیت استفاده شده است. به منظور طراحی سیستم فازی برای محاسبه مقدار CMRR تنها متغیرهای کمی (مقاومت فشاری تک‌محوره، فاصله‌داری و پایایی درزه) به عنوان پارامترهای ورودی سیستم فازی در نظر گرفته شده است. در نهایت مقدار CMRR و FCMRR برای چهار بخش از معدن ریکال محاسبه و با هم مقایسه شده است.

کلمات کلیدی: CMRR، فازی نوع ۲، ، معادن زغال‌سنگ، FCMRR.